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Submission date: 25-Apr-2024 02:24PM (UTC+0700)
Submission ID: 2361274298
File name: Artikel.docx (390.84K)
Word count: 3562
Character count: 19456

Classification of Papilledema Disease Based on Texture Features of Retinal Fundus Images Using Machine Learning Methods

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Abstrak- Papilledema, characterized by swelling of the optic disc retina, results from constant intracranial pressure increase, often due to elevated cerebrospinal fluid in the brain and optic nerve. Prompt and accurate diagnosis is essential to prevent potential permanent vision damage. This study aims to identify the most optimal texture features from fundus images to build a machine learning model. This process involves classifying fundus images based on texture feature extraction from the optic disc and blood vessels. The methodology consists of several stages. First, fundus image datasets are processed to extract texture features using the Grey Level Difference Method (GLDM). Subsequently, blood vessel fundus images are segmented using the Tyler Coye algorithm, followed by Tamura feature extraction. The final step involves classifying the extracted features using two methods, namely Support Vector Machine with RBF kernel (SVM-RBF) and K-Nearest Neighbors with Particle Swarm Optimization (KNN-PSO). Additionally, the study aims to evaluate the classification performance of fundus images using SVM and KNN algorithms, measuring precision, recall, accuracy, and F1-score as primary evaluation metrics to ensure the validity and effectiveness of the developed model. Evaluation results indicate that KNN performs better in handling imbalanced data scenarios, while SVM is more effective in downsampling scenarios. Combined features achieve the highest accuracy of 95% in downsampling scenarios, while GLDM features yield the best results with 94% accuracy in other scenarios. Thus, GLDM features are proven effective in enhancing classification performance, especially when used with SVM.

Keywords- papilledema, classification, machine learning, GLDM, Tamura features

I. INTRODUCTION

Papilledema, characterized by swelling of the optic disc retina, is caused by consistent intracranial pressure increase due to cerebrospinal fluid accumulation in the brain and optic nerves [1]. This condition often serves as an indicator of other serious diseases such as brain tumors, brain edema, or increased cerebrospinal pressure [2]. Diagnosis of papilledema is typically performed by ophthalmologists or neuro-ophthalmologists through ocular physical examinations, utilizing tools such as ophthalmoscopes, CT scans, MRI, and ultrasound [3]. The importance of prompt diagnosis and management is highlighted as delays can lead to permanent vision damage [4]. Therefore, optimization of technology and development of new methods are necessary for faster and more efficient papilledema detection. Machine learning technology, especially SVM and KNN, has been successfully used in classifying other eye conditions with high accuracy [5], [6].

This study employs computer vision as part of artificial intelligence, where algorithms are developed to automatically extract features from visual objects [7]. Papilledema fundus images have featureless optic disc with darker optic nerves compared to normal fundus images. Therefore, texture feature extraction can aid in classifying normal and papilledema fundus images [3].The texture feature extraction method used in this study is Grey Level Different Method (GLDM) with 5 features, namely contrast, angular second moment, entropy, mean, and inverse different moment. GLDM method and these five features have previously been successfully used to classify normal and abnormal diabetic retinopathy fundus images with 95% accuracy using KNN classification method [6].

Papilledema also affects blood vessel formation, where blood vessels at the optic nerve head (ONH) enlarge and blood vessels become blurred due to edematous Retinal Nerve Fiber Layer (RNFL). A normal retina has some discontinuous blood vessels in the blood vessel segmentation image, but in papilledema, there are more discontinuous areas due to vessel blurring [3]. Therefore, texture feature extraction from blood vessel segmentation images can assist in classifying normal and papilledema fundus images. Tyler Coye algorithm is used for blood vessel segmentation in this study. Three texture features are extracted, namely coarseness, contrast, and directionality, using the Tamura Feature algorithm, as done in previous studies by Barges and Thabet in

classifying normal and abnormal diabetic retinopathy fundus images with the highest accuracy of 100% [6]. SVM and KNN classification methods are used to identify papilledema, and each classifier is tested on features from each extraction technique as well as combined features from both extraction techniques for effective comparison based on accuracy.

Kernel RBF is chosen for use in SVM because of its ability to handle complex and non-linear data. This kernel allows SVM to map data into a feature space with infinite dimensions, thereby capturing complex and non-linear patterns in data [8]. Determining the optimal value of k in the KNN algorithm has significant impact and is often challenging, especially in complex and varied data. To address this, several studies have proposed metaheuristic approaches, including PSO (Particle Swarm Optimization), to automatically find the optimal k value. In the context of KNN, PSO can be used to find the k value that maximizes classification performance based on specific objective functions, such as classification accuracy or cross-validation. Empirical research has shown that PSO approach in adjusting the k parameter in KNN can significantly improve classification performance, especially on complex and large datasets [9], [10].

This study will evaluate system performance using standard metrics such as accuracy, precision, recall, and F1-score. Finally, cross-validation will be performed using K-Fold to evaluate model performance and avoid overfitting. The number of folds used is 5. It is hoped that this research can make a significant contribution to preventing blindness due to papilledema by providing more effective and rapid diagnostic methods.

II. DATA

The fundus image data were sourced from Kim's research titled "Machine Learning for Pseudopapilledema" [11]. The dataset comprises 779 images labeled as normal, 295 images labeled as papilledema, and 295 images labeled as pseudo-papilledema. All images in the dataset are retinal fundus images in JPG format with dimensions of 240 x 240 pixels. In their study, the fundus image dataset had been preprocessed by cropping around the optic disc area.

III. METHODOLOGY

The research stages outline the framework of a study to understand systematically the activities conducted. This step is carried out to address a problem and achieve the expected goals. Figure 1 illustrates the research stages conducted.

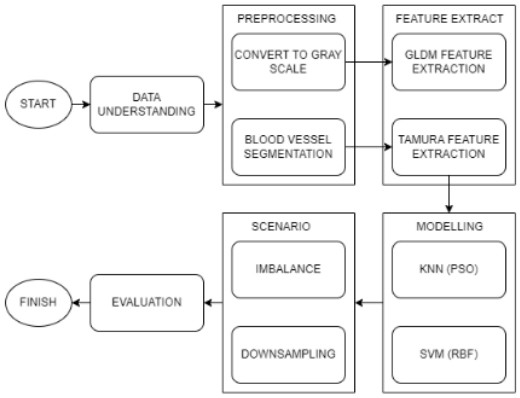

Figure 1. Research stages

Data Understanding

Data Understanding is the initial stage aimed at understanding the data to be processed. The identified aspects in this stage include identifying issues in images and understanding the dataset description such as the length and width dimensions of the images, the number of labels, and the visual differences in image representation for each label.

Preprocessing

The activities conducted in this stage involve converting fundus images into Gray Scale Conversion and performing Image Segmentation using the Tyler Coye method.

a. *Convert to Gray Scale*

This stage involves converting the color image data into a grayscale image. This is done because the subsequent process involves texture feature extraction using GLDM, which requires grayscale image input. The Gray Scale process is performed using the Scikit Image Library (Skimage).'

a. *Blood Vessel Segmentation with Tyler Coye*

The Tyler Coye method is utilized as the segmentation approach. The first step in this segmentation process is to take the original image from the dataset as input. Then, the image is processed using the Tyler Coye method, which involves several steps such as converting to grayscale with principal component analysis (PCA), contrast enhancement with adaptive histogram equalization, and background exclusion by subtracting the mean-filtered image. Binarization is performed using the ISODATA method to obtain a binary image indicating blood vessels. Afterward, texture features such as Tamura Features are extracted from the resulting binary image for use in the classification stage.

During the blood vessel segmentation process, adjustments to the threshold level may be made to obtain the best segmentation results. Adjusting the threshold level can be done by testing several threshold values and selecting the value that produces the best segmentation results. This stage is crucial to ensure that the resulting blood vessel segmentation meets the research needs and supports the overall accuracy of papilledema fundus image classification.

Feature Extraction

The feature extraction stage aims to extract texture feature data from the images resulting from preprocessing activities. The features extracted from GLDM extraction are Contrast, Angular Second Moment (ASM), Entropy, Mean, and Inverse Different Moment (IDM). Meanwhile, the features extracted from Tamura Feature extraction are coarseness, contrast, and directionality. Thus, there are a total of eight features to be used as attributes in the classification process.

Modeling and Scenario

In this study, the dataset will be divided into several ratios of training data and testing data. The data training and testing ratio used is 7:3 and 8:2. In model development, each KNN and SVM classifier will be used to train the model using data from the training data. Then, the testing data is used for the evaluation process of the designed model.

The k value in KNN is determined through Particle Swarm Optimization (PSO) algorithm. The kernel used in SVM is the RBF kernel with the parameter C determined through the parameter tuning process. Each classifier is tested on features from each extraction technique and also combined features from the results of both extraction techniques to obtain an effective comparison based on accuracy values.

Evaluation

In this stage, evaluation of the modeling results will be conducted to assess how well the built model performs in classification. Several aspects calculated in the evaluation stage include accuracy, precision, recall, and F1-score values. Finally, cross-validation using K-Fold will be performed to evaluate the model's performance and avoid overfitting. The number of folds used is 5.

IV. RESULT

Data Understanding

The dataset consists of fundus retina images that have undergone cropping to capture the area around the optic disc. Illustrated in Figures 2 and 3 are examples of normal fundus retina images and papilledema fundus retina images, respectively.

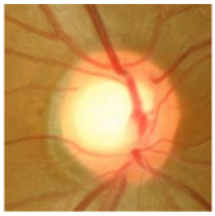

Figure 2. Normal fundus retinal image

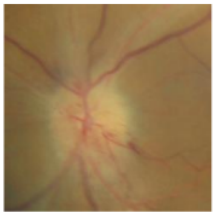

Figure 3. Papilledema fundus retinal image

Papilledema fundus retina images exhibit an optic disc with optic nerve fibers that have a more blurred and darker edge compared to normal fundus retina images. Papilledema also affects the formation of blood vessels, where the veins at the optic nerve head (ONH) enlarge, and blood vessels are blurred due to edematous Retinal Nerve Fiber Layer (RNFL).

From a total of 779 normal fundus image data, one data appears blurry, as shown in Figure 4. In the papilledema class, there are four data with blurry conditions, visible in Figure 5. This image condition can lead to segmentation failure due to blurry image quality [12].

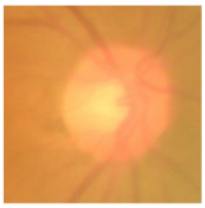

Figure 4. Normal fundus retina image with blurred conditions

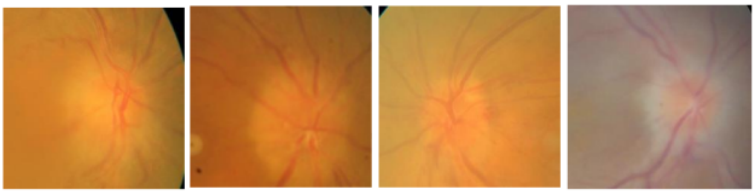

Figure 5. Fundus papilledema images with blurred conditions

Preprocessing

In this stage, the data is prepared before entering the feature extraction phase. The following are the preprocessing steps undertaken:

a. Convert to Gray Scale

In this step, color fundus images are converted into grayscale images using the Scikit Image Library (Skimage). Figure 6 below shows the result of converting color fundus images into grayscale images.

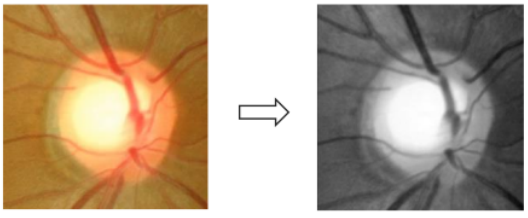

Figure 6. Convert to gray scale.

b. Blood Vessel Segmentation with Tyler Coye

This step is performed to obtain blood vessel images from fundus images. Several actions are taken in the blood vessel segmentation step:

1. Converting color fundus images into grayscale images using PCA.
2. Performing contrast enhancement on the input grayscale fundus images with CLAHE using the adapthisteq function.
3. Performing background exclusion.
4. Converting the resulting background exclusion image into a binary image where all pixels in the input image exceeding the threshold value are replaced with the number 1, and the rest are replaced with the number 0.
5. Removing small objects from the binary image. This is done by calculating the area of adjacent 1 values and replacing them with 0 if their area is less than or equal to the given parameter. In this method, objects are removed if their area is less than or equal to 100.
6. The binary image that has undergone the removal of small objects is then converted entirely, and the values are saved into variable BW2. The values that were previously 1 are changed to 0, and vice versa. The output of the segmentation process is produced from an overlay process where all pixels from the input color fundus image are changed to black in places where the binary input mask BW2 is valued at 1 or true.

The threshold value is calculated using the ISODATA method. The output of the segmentation images with the threshold level calculated using ISODATA may result in noise in some images, as shown in Figure 7. To address this issue, the threshold level is increased by a value of 0.02 for every segmentation process across the entire dataset. Increasing the threshold level by a value of 0.02 is also able to exclude blurry blood vessels due to swelling in the optic disc area in papilledema fundus images. The output of blood vessel segmentation after the threshold level is increased by 0.02 is displayed in Figure 8.

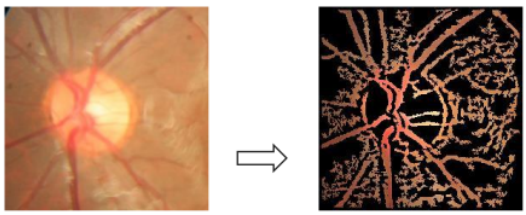

Figure 7. Blood vessel segmentation without adding a threshold level.

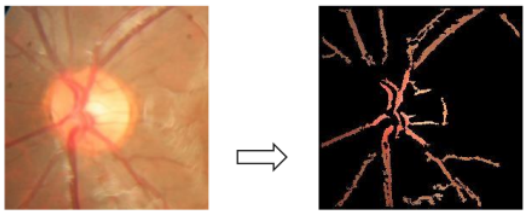

Figure 8. Blood vessel segmentation with a threshold level + 0.02.

Out of a total of 779 normal fundus image data, 1 data shown in Figure 4 failed during the segmentation process. In the papilledema class, there are also 4 images shown in Figure 5 that failed to be segmented. The cause of these failures is the poor quality of the images, resulting in inaccurate threshold calculations.

Feature Extraction

During the feature extraction stage, the process involves extracting image data from the preprocessing stage. The output from the gray level conversion using the Scikit-Image Library (Skimage) is then extracted into tabular data using feature calculations from GLDM, including contrast, angular second moment, entropy, mean, and inverse different moment.

The output data from the blood vessel segmentation process is also extracted into tabular data using feature calculations from Tamura Feature, including coarseness, contrast, and directionality.

Modelling dan Scenario

In the subsequent classification stage, the tabular data resulting from feature extraction will be subjected to classification. The ratio of data training to data testing used is 7:3 and 8:2. The testing process is divided into three parts: using GLDM features, using Tamura Feature, and using a combination of GLDM and Tamura Feature. In the testing process, each test is conducted under two scenarios: imbalance and downsampling. The models used are K-Nearest Neighbor with Particle Swarm Optimization (PSO) and Support Vector Machine with the RBF kernel.

The parameter C in SVM is determined through parameter tuning methods. Figure 9 shows the changes in test score values concerning the parameter C in the imbalance data.

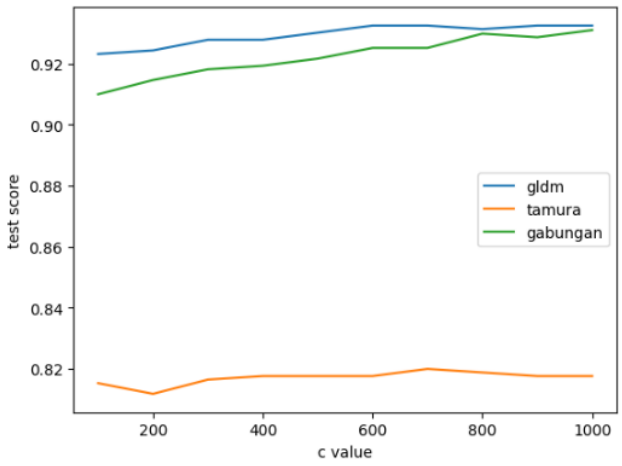

Figure 9. Tuning C Parameter

Figure 9 shows that the increase in test score tends to be proportional to the increase in the value of parameter C for GLDM features and the combined ones. However, the test score values do not indicate significant differences across different implementations of C values. This suggests that the model is relatively stable and consistent in its performance.

Evaluation

In the evaluation phase, the accuracy, precision, recall, and F1-Score values of the models trained in the previous stages will be calculated. This evaluation is conducted in three scenarios: testing using GLDM features, features from Tamura, and the combination of GLDM and Tamura features. Tables 1 and 2 show the performance results of the built classification models.

Table 1. Presents the evaluation results with a data training to data testing ratio of 7:3.

No	Skenario	Fitur Ekstraksi	*Classifier*	*Accuracy*	*Precision*	*Recall*	*F1-Score*
1	*Imbalance*	GLDM	SVM	0.92	0.92	0.92	0.92
2			KNN	0.89	0.89	0.89	0.89

3		Tamura	SVM	0.79	0.78	0.79	0.78
4			KNN	0.75	0.74	0.75	0.71
5		Gabungan	SVM	0.91	0.91	0.91	0.91
6			KNN	0.89	0.89	0.89	0.88
7	*Downsampling*	GLDM	SVM	0.93	0.93	0.93	0.93
8			KNN	0.88	0.88	0.89	0.88
9		Tamura	SVM	0.80	0.80	0.80	0.80
10			KNN	0.73	0.73	0.73	0.73
11		Gabungan	SVM	0.92	0.92	0.92	0.92
12			KNN	0.89	0.89	0.88	0.88

Table 2. Presents the evaluation results with a data training to data testing ratio of 8:2.

No	Skenario	Fitur Ekstraksi	*Classifier*	*Accuracy*	*Precision*	*Recall*	*F1-Score*
1	*Imbalance*	GLDM	SVM	0.94	0.94	0.94	0.94
2			KNN	0.93	0.94	0.93	0.93
3		Tamura	SVM	0.79	0.78	0.79	0.78
4			KNN	0.76	0.74	0.76	0.73
5		Gabungan	SVM	0.92	0.92	0.92	0.92
6			KNN	0.90	0.90	0.90	0.90
7	*Downsampling*	GLDM	SVM	0.94	0.94	0.94	0.94
8			KNN	0.89	0.89	0.90	0.89
9		Tamura	SVM	0.82	0.82	0.82	0.82
10			KNN	0.74	0.74	0.74	0.73
11		Gabungan	SVM	0.95	0.95	0.95	0.95
12			KNN	0.88	0.88	0.88	0.88

om Table 1 and Table 2, it can be observed that the evaluation scores of the model applied to GLDM features are higher compared to the model applied to features extracted from the segmentation of blood vessel images using Tamura Feature. Testing GLDM features achieved the highest accuracy when using the SVM kernel RBF model with a data training to data testing ratio of 8:2, reaching 0.94 in the downsampling scenario. The best accuracy in testing GLDM features had the same value in both the imbalance and downsampling scenarios with the SVM kernel RBF model at a data ratio of 8:2. Testing Tamura features yielded the highest accuracy of 0.82 with a data training to data testing ratio of 8:2 using the SVM kernel RBF model in the downsampling scenario. The combination of both features resulted in the highest accuracy of 0.95 when using the SVM kernel RBF model in the downsampling scenario with a data ratio of 8:2.

Dividing the data with train-test split can provide a quick estimate of model performance, but the results may vary depending on how the data is partitioned, especially with small datasets. Therefore, cross-validation using K-Fold was conducted to provide an overview of the model's performance on the entire dataset, with the results presented in Table 3.

Table 3. Presents the evaluation results with K-Fold cross-validation.

No	Skenario	Fitur Ekstraksi	*Classifier*	*Accuracy*	*Precision*	*Recall*	*F1-Score*

1	*Imbalance*	GLDM	SVM	0.93	0.86	0.89	0.87
2			KNN	0.90	0.90	0.90	0.90
3		Tamura	SVM	0.81	0.72	0.48	0.59
4			KNN	0.78	0.77	0.78	0.76
5		Gabungan	SVM	0.91	0.84	0.87	0.85
6			KNN	0.91	0.91	0.91	0.91
7	*Downsampling*	GLDM	SVM	0.92	0.90	0.95	0.92
8			KNN	0.89	0.89	0.89	0.89
9		Tamura	SVM	0.75	0.79	0.72	0.73
10			KNN	0.74	0.74	0.74	0.74
11		Gabungan	SVM	0.92	0.90	0.95	0.92
12			KNN	0.89	0.89	0.89	0.89

From Table 3, it can be observed that the KNN classifier produces better precision, recall, and F1-score values than SVM in the imbalance scenario. This indicates that KNN is capable of handling imbalanced data better than SVM. Conversely, in the downsampling scenario, the SVM classifier demonstrates superior evaluation scores compared to the use of the KNN classifier.

V. CONCLUSION

Based on the cross-validation evaluation results with K-Fold, the performance of the KNN algorithm is better than SVM in handling the data imbalance scenario, with higher precision, recall, and F1 scores compared to the use of the SVM classifier. In the downsampling scenario, SVM demonstrates better performance than KNN. The best classification performance is achieved by the combined features with 95% accuracy in the downsampling scenario with a data ratio of 8:2. Meanwhile, GLDM feature extraction yields the best performance in the remaining scenarios, with the highest accuracy of 94% using the SVM classifier. GLDM features show the best results in the cross-validation process with the highest accuracy of 93% in the imbalance scenario and 92% in the downsampling scenario using the SVM classifier.

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